

Titanic

May 2, 2024

1 TITANIC E I SOPPRAVVISSUTI

1.1 CREATO DA GRANIERI JOELE, TASSONE LEONARDO, RAPHAEL RODRIGO E RADISHA WARNAKULASURIYA

1.1.1 IMPORTAZIONE DEI DATI DA OSSERVARE

```
[1]: import pandas as pd
titanic = pd.read_csv("C:\\Users\\joele\\OneDrive\\Desktop\\dati_
↳robotica\\gender_submission.csv")
titanic
```

```
[1]:      PassengerId  Survived
0             892           0
1             893           1
2             894           0
3             895           0
4             896           1
..          ...      ...
413           1305           0
414           1306           1
415           1307           0
416           1308           0
417           1309           0
```

[418 rows x 2 columns]

```
[2]: import pandas as pd
titanic = pd.read_csv("C:\\Users\\joele\\OneDrive\\Desktop\\dati_robotica\\test.
↳csv")
titanic
```

```
[2]:      PassengerId  Pclass                                Name \
0             892         3                      Kelly, Mr. James
1             893         3      Wilkes, Mrs. James (Ellen Needs)
2             894         2          Myles, Mr. Thomas Francis
3             895         3                Wirz, Mr. Albert
4             896         3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)
```

```

..      ...      ...
413      1305      3      Spector, Mr. Woolf
414      1306      1      Oliva y Ocana, Dona. Fermina
415      1307      3      Saether, Mr. Simon Sivertsen
416      1308      3      Ware, Mr. Frederick
417      1309      3      Peter, Master. Michael J

      Sex  Age  SibSp  Parch      Ticket      Fare  Cabin  Embarked
0      male  34.5      0      0      330911      7.8292  NaN      Q
1      female  47.0      1      0      363272      7.0000  NaN      S
2      male  62.0      0      0      240276      9.6875  NaN      Q
3      male  27.0      0      0      315154      8.6625  NaN      S
4      female  22.0      1      1      3101298      12.2875  NaN      S
..      ...      ...      ...      ...      ...      ...      ...
413      male  NaN      0      0      A.5. 3236      8.0500  NaN      S
414      female  39.0      0      0      PC 17758      108.9000  C105      C
415      male  38.5      0      0      SOTON/O.Q. 3101262      7.2500  NaN      S
416      male  NaN      0      0      359309      8.0500  NaN      S
417      male  NaN      1      1      2668      22.3583  NaN      C

```

[418 rows x 11 columns]

```

[3]: import pandas as pd
titanic = pd.read_csv("C:\\Users\\joele\\OneDrive\\Desktop\\dati\\robotica\\train.csv")
titanic

```

```

[3]:      PassengerId  Survived  Pclass  \
0              1         0         3
1              2         1         1
2              3         1         3
3              4         1         1
4              5         0         3
..      ...      ...      ...
886          887         0         2
887          888         1         1
888          889         0         3
889          890         1         1
890          891         0         3

```

```

      Name      Sex  Age  SibSp  \
0      Braund, Mr. Owen Harris      male  22.0      1
1      Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2      Heikkinen, Miss. Laina      female  26.0      0
3      Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4      Allen, Mr. William Henry      male  35.0      0
..      ...      ...      ...      ...

```

886		Montvila, Rev. Juozas	male	27.0	0
887		Graham, Miss. Margaret Edith	female	19.0	0
888		Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1
889		Behr, Mr. Karl Howell	male	26.0	0
890		Dooley, Mr. Patrick	male	32.0	0

	Parch	Ticket	Fare	Cabin	Embarked
0	0	A/5 21171	7.2500	NaN	S
1	0	PC 17599	71.2833	C85	C
2	0	STON/O2. 3101282	7.9250	NaN	S
3	0	113803	53.1000	C123	S
4	0	373450	8.0500	NaN	S
..
886	0	211536	13.0000	NaN	S
887	0	112053	30.0000	B42	S
888	2	W./C. 6607	23.4500	NaN	S
889	0	111369	30.0000	C148	C
890	0	370376	7.7500	NaN	Q

[891 rows x 12 columns]

1.1.2 CONTROLLO DELLE PRIME RIGHE DEI PASSEGGERI

```
[4]: titanic.head()
```

```
[4]: PassengerId  Survived  Pclass  \
0             1         0       3
1             2         1       1
2             3         1       3
3             4         1       1
4             5         0       3
```

	Name	Sex	Age	SibSp	\
0	Braund, Mr. Owen Harris	male	22.0	1	
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	
2	Heikkinen, Miss. Laina	female	26.0	0	
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
4	Allen, Mr. William Henry	male	35.0	0	

	Parch	Ticket	Fare	Cabin	Embarked
0	0	A/5 21171	7.2500	NaN	S
1	0	PC 17599	71.2833	C85	C
2	0	STON/O2. 3101282	7.9250	NaN	S
3	0	113803	53.1000	C123	S
4	0	373450	8.0500	NaN	S

1.1.3 CONTROLLO DELL'ETA' DEI PASSEGGERI

```
[5]: mean_age = titanic['Age'].mean()
titanic['Age'].fillna(mean_age, inplace=True)
titanic['Age']
```

```
[5]: 0      22.000000
1      38.000000
2      26.000000
3      35.000000
4      35.000000
...
886    27.000000
887    19.000000
888    29.699118
889    26.000000
890    32.000000
Name: Age, Length: 891, dtype: float64
```

qui controlliamo l'età dei passeggeri e sostituiamo le età mancanti con .fillna calcolando la media

1.1.4 CONTROLLO DEI COSTI DEI BIGLIETTI

```
[6]: titanic['Fare'].fillna(method='ffill', inplace=True)
titanic['Fare']
```

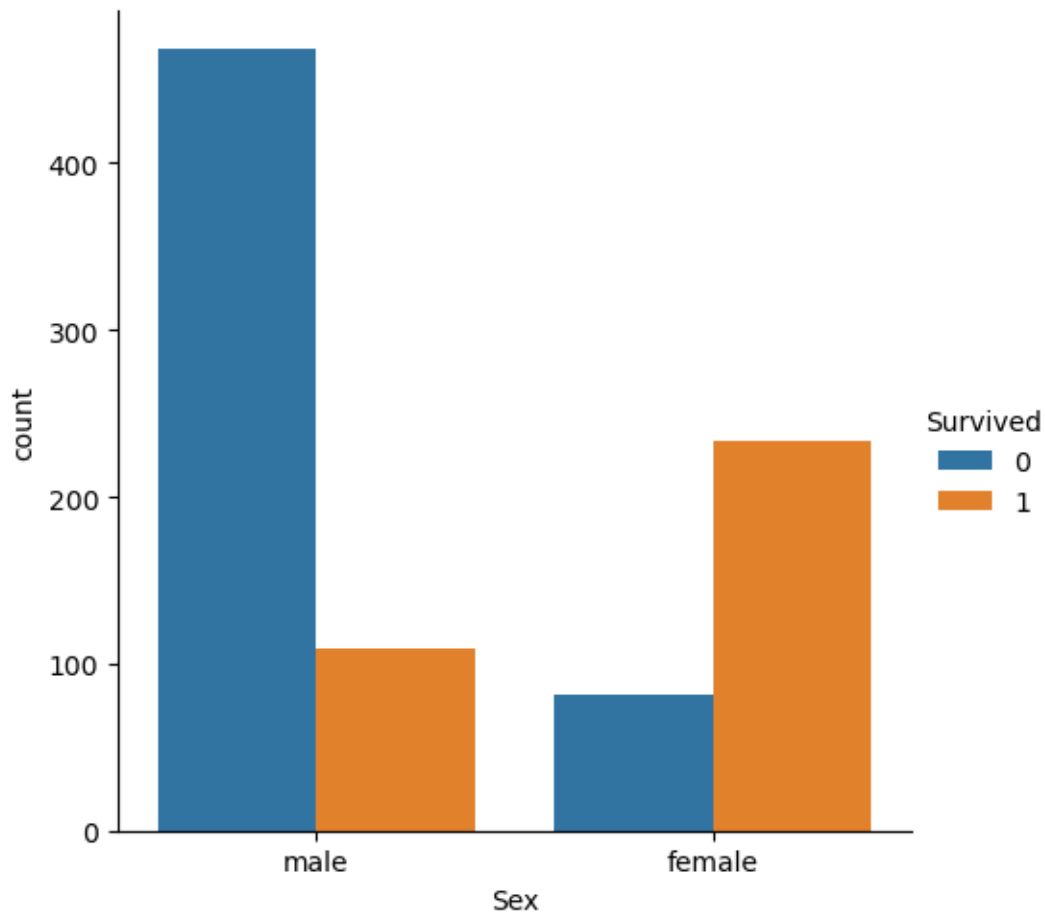
```
[6]: 0      7.2500
1     71.2833
2      7.9250
3     53.1000
4      8.0500
...
886    13.0000
887    30.0000
888    23.4500
889    30.0000
890     7.7500
Name: Fare, Length: 891, dtype: float64
```

qui invece vediamo i prezzi dei biglietti e sostituiamo i costi mancanti sempre con .fillna calcolando la media dei costi

1.1.5 GRAFICO A BARRE SUI SOPRAVVISUTI E I MORTI TRA MASCHI E FEMMINE

```
[7]: import seaborn as sns
import matplotlib.pyplot as plt
sns.catplot(x="Sex", hue="Survived", kind="count", data=titanic)
```

```
[7]: <seaborn.axisgrid.FacetGrid at 0x1aef89e5a90>
```

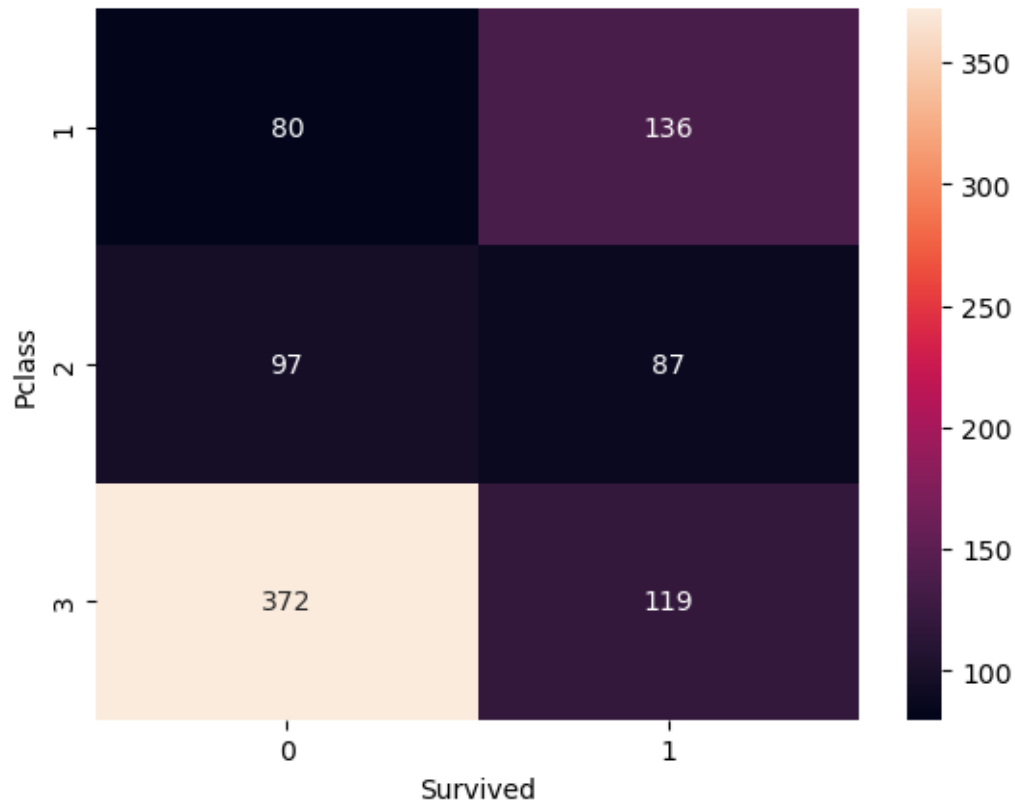


adesso creiamo un grafico a barre prendendo i maschi e le femmine e come valore per l'asse y il numero delle persone e creiamo una colonna blu per il numero di morti e una arancione per il numero dei sopravvissuti

1.1.6 CONTROLLO CON HEATMAP DEI MORTI-SOPRAVVISSUTI TRA LE DIVERSE CLASSI

```
[8]: group = titanic.groupby(['Pclass', 'Survived'])
pclass_survived = group.size().unstack()
sns.heatmap(pclass_survived, annot=True, fmt="d")
```

```
[8]: <Axes: xlabel='Survived', ylabel='Pclass'>
```

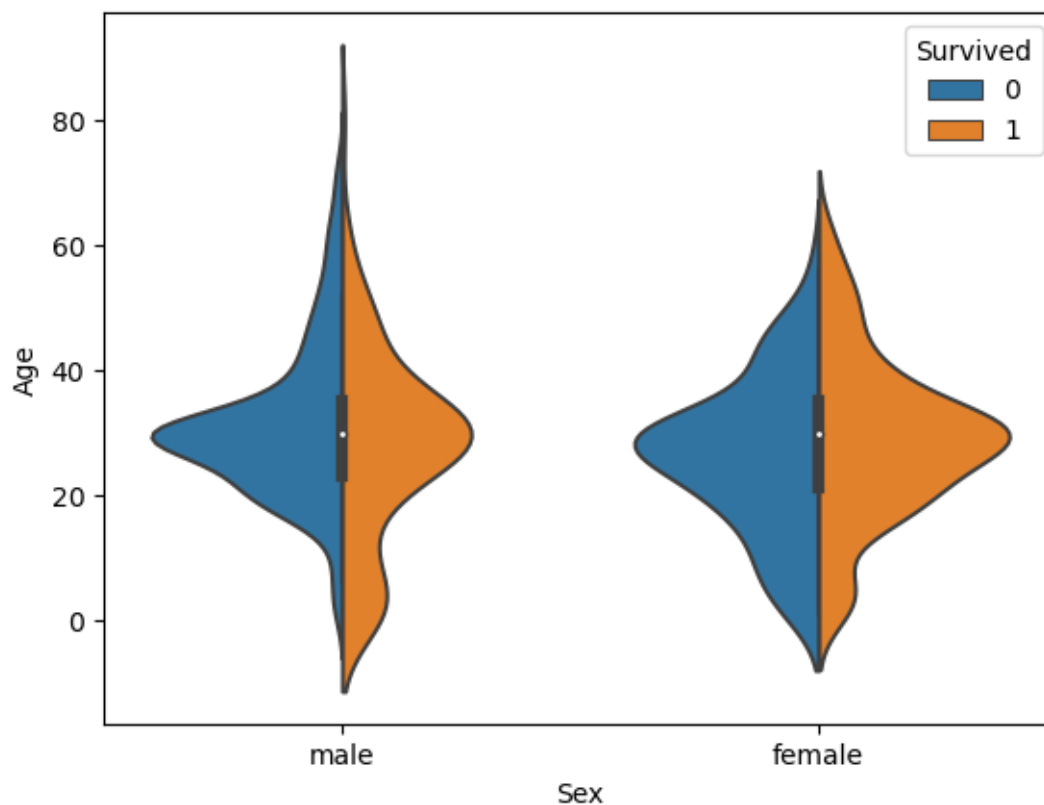


qui abbiamo una heatmap dove è rappresentato sull'asse y la classe di appartenenza e si nota con abbastanza facilità che in terza classe ci sono la maggior parte dei morti dell'intera imbarcazione, in seconda sono abbastanza bilanciati morti e sopravvissuti e invece in prima classe si sono salvate molte più persone rispetto a quelle decedute

1.1.7 CONTROLLO CON GRAFICO A VIOLINO DEI MORTI-SOPRAVVISUTI TRA MASCHI E FEMMIEN E LA LORO ETA'

```
[9]: sns.violinplot(x="Sex", y="Age", hue="Survived", data=titanic, split=True)
```

```
[9]: <Axes: xlabel='Sex', ylabel='Age'>
```



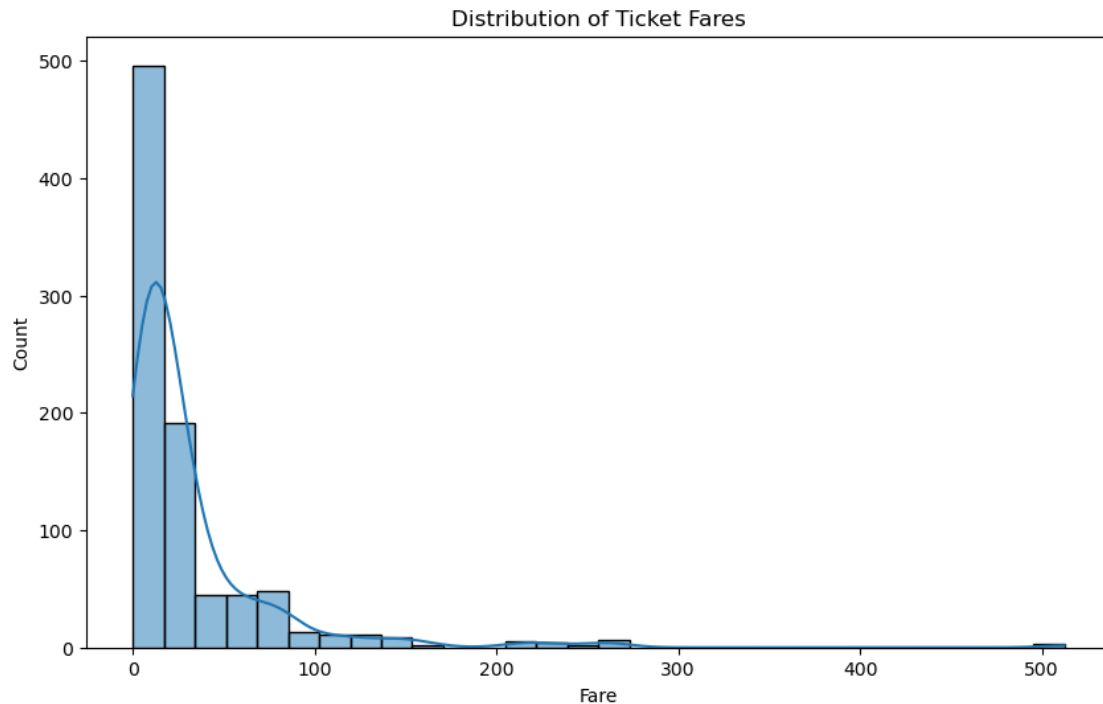
1.1.8 CONTROLLO DEI TITOLI DI OGNI PASSEGGERO

```
[10]: titanic['Title'] = titanic['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)
      titanic['Title']
```

```
[10]: 0      Mr
      1      Mrs
      2      Miss
      3      Mrs
      4      Mr
      ...
      886     Rev
      887     Miss
      888     Miss
      889      Mr
      890      Mr
      Name: Title, Length: 891, dtype: object
```

1.1.9 GRAFICO A DISTRIBUZIONE SUL COSTO DEI BIGLIETTI E DI QUANTI SONO STATI VENDUTI

```
[11]: plt.figure(figsize=(10, 6))
sns.histplot(titanic['Fare'], bins=30, kde=True)
plt.xlabel('Fare')
plt.ylabel('Count')
plt.title('Distribution of Ticket Fares')
plt.show()
```



qui abbiamo un grafico a distribuzione sui costi e i biglietti venduti

1.1.10 CONTROLLO DELLA PERCENTUALE DI SOPRAVVISUTI NELLE DIVERSE FASCE D'ETA'

```
[12]: titanic['AgeGroup'] = pd.cut(titanic['Age'], bins=[0, 18, 30, 50, 100],
    labels=['0-18', '19-30', '31-50', '51+'])
age_survival = titanic.groupby('AgeGroup')['Survived'].mean()
print(age_survival)
```

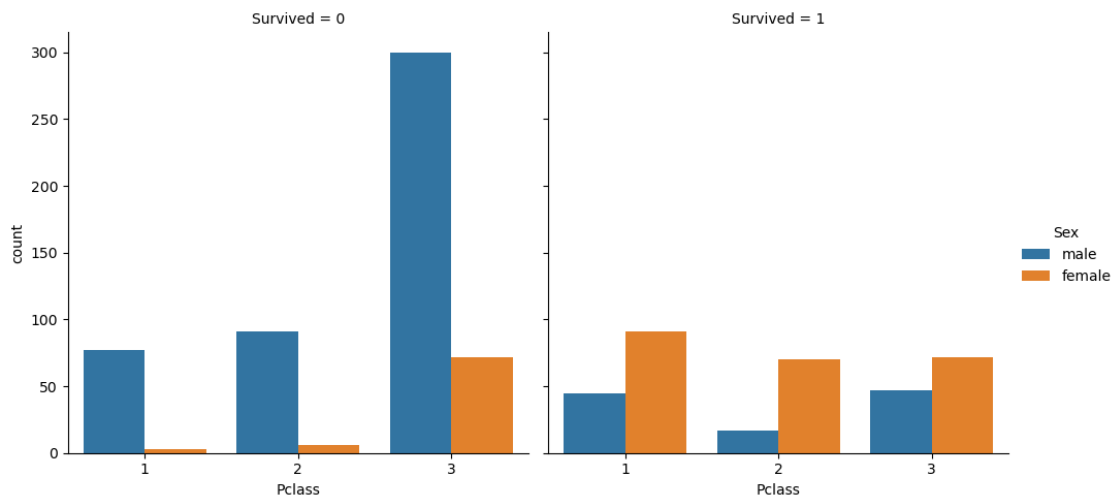
```
AgeGroup
0-18      0.503597
19-30     0.331096
31-50     0.423237
51+       0.343750
```


Name: Survived, dtype: float64

1.1.11 CONTROLLO CON GRAFICO A BARRE DI SOPRAVVISSUTI O MORTI TRA LE DIVERSE CLASSI E IL LORO SESSO

```
[13]: sns.catplot(x="Pclass", hue="Sex", col="Survived", kind="count", data=titanic)
```

```
[13]: <seaborn.axisgrid.FacetGrid at 0x1aef92c5fd0>
```



1.1.12 PERCENTUALE SOPRAVVISUTI DA OGNI PORTO DI IMBARCO

```
[14]: embarked_survival = titanic.groupby('Embarked')['Survived'].mean()
print(embarked_survival)
```

Embarked

C 0.553571

Q 0.389610

S 0.336957

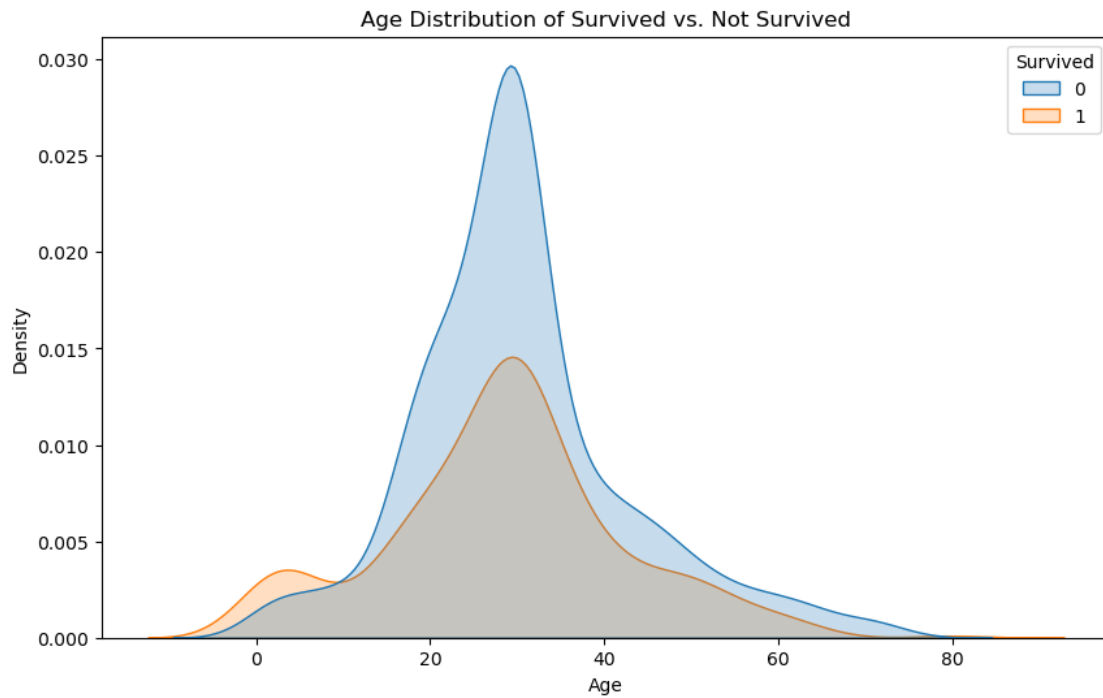
Name: Survived, dtype: float64

percentuali di sopravvissuti dai diversi porti di imbarco. (C = Cherbourg ; Q = Queenstown; S = Southampton)

1.1.13 GRAFICO DELLA DISTRIBUZIONE DEI SOPRAVVISSUTI O MORTI E LA LORO ETA'

```
[15]: plt.figure(figsize=(10, 6))
sns.kdeplot(data=titanic, x='Age', hue='Survived', fill=True)
plt.xlabel('Age')
plt.ylabel('Density')
plt.title('Age Distribution of Survived vs. Not Survived')
```

```
plt.show()
```



1.1.14 CONTROLLO PERCENTUALE DI SOPRAVVISSUTI PER OGNI TITOLO

```
[16]: title_survival = titanic.groupby('Title')['Survived'].mean()  
print(title_survival)
```

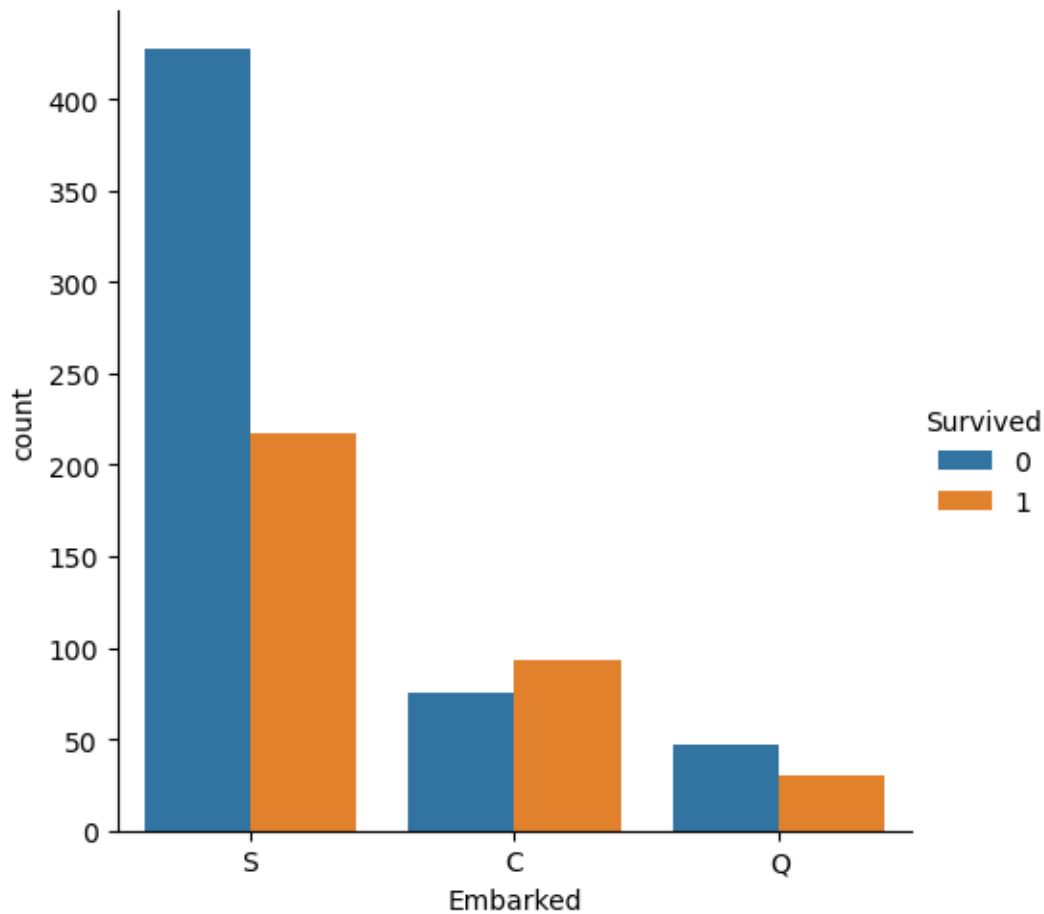
Title	
Capt	0.000000
Col	0.500000
Countess	1.000000
Don	0.000000
Dr	0.428571
Jonkheer	0.000000
Lady	1.000000
Major	0.500000
Master	0.575000
Miss	0.697802
Mlle	1.000000
Mme	1.000000
Mr	0.156673
Mrs	0.792000
Ms	1.000000
Rev	0.000000
Sir	1.000000

Name: Survived, dtype: float64

1.1.15 CONTROLLO MORTI-SOPPRAVVISUTI TRA I PASSEGGERI E DA DOVE SI SONO IMBARCATI

```
[17]: sns.catplot(x="Embarked", hue="Survived", kind="count", data=titanic)
```

```
[17]: <seaborn.axisgrid.FacetGrid at 0x1ae80213590>
```



1.1.16 CONTROLLO PERCENTUALE SOPRAVVISSUTI TRA LE DIVERSE FASCE DI ETA' E TRA MASCHI E FEMMINE

```
[18]: age_sex_survival = titanic.groupby(['AgeGroup', 'Sex'])['Survived'].mean()  
print(age_sex_survival)
```

AgeGroup	Sex	Survived
0-18	female	0.676471
	male	0.338028
19-30	female	0.727273

```

        male      0.144737
31-50   female    0.779070
        male      0.225806
51+     female    0.941176
        male      0.127660
Name: Survived, dtype: float64

```

1.1.17 CONTROLLO PERCENTUALE SOPRAVVIVENZA TRA I DIVERSI TITOLI E DA DOVE SI SONO IMBARCATI

```
[19]: title_class_survival = titanic.groupby(['Title', 'Pclass'])['Survived'].mean()
      print(title_class_survival)
```

```

Title      Pclass
Capt      1      0.000000
Col         1      0.500000
Countess   1      1.000000
Don         1      0.000000
Dr          1      0.600000
           2      0.000000
Jonkheer   1      0.000000
Lady        1      1.000000
Major       1      0.500000
Master      1      1.000000
           2      1.000000
           3      0.392857
Miss        1      0.956522
           2      0.941176
           3      0.500000
Mlle        1      1.000000
Mme         1      1.000000
Mr          1      0.345794
           2      0.087912
           3      0.112853
Mrs         1      0.976190
           2      0.902439
           3      0.500000
Ms          2      1.000000
Rev         2      0.000000
Sir         1      1.000000
Name: Survived, dtype: float64

```

1.1.18 CODIFICAZIONE DEL DATAFRAME CON ONEHOTENCODER

```
[20]: from sklearn.preprocessing import OneHotEncoder

      # Seleziona solo le colonne categoriche nel DataFrame
      categorical_columns = titanic.select_dtypes(include=['object'])
```

```

# Inizializza OneHotEncoder
encoder = OneHotEncoder()

# Applica l'encoding alle colonne categoriche e trasforma i dati
encoded_categorical_columns = encoder.fit_transform(categorical_columns)

# Ottieni i nomi delle categorie dall'encoder
encoded_categories = encoder.categories_

encoded_column_names = []
for i, col in enumerate(categorical_columns.columns):
    encoded_column_names.extend([f"{col}_{category}" for category in
    ↪ encoded_categories[i]])

# Crea un nuovo DataFrame con le colonne categoriche codificate e i nomi delle
    ↪ colonne
df2_encoded = pd.DataFrame(encoded_categorical_columns.toarray(),
    ↪ columns=encoded_column_names)

# Visualizza il nuovo DataFrame codificato
print(df2_encoded)

```

	Name_Abbing, Mr. Anthony	Name_Abbott, Mr. Rossmore Edward \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0
890	0.0	0.0

	Name_Abbott, Mrs. Stanton (Rosa Hunt)	Name_Abelson, Mr. Samuel \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0

890	0.0	0.0
-----	-----	-----

	Name_Abelson, Mrs. Samuel (Hannah Wizosky) \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
886	0.0
887	0.0
888	0.0
889	0.0
890	0.0

	Name_Adahl, Mr. Mauritz Nils Martin	Name_Adams, Mr. John \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0
890	0.0	0.0

	Name_Ahlin, Mrs. Johan (Johanna Persdotter Larsson) \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
886	0.0
887	0.0
888	0.0
889	0.0
890	0.0

	Name_Aks, Mrs. Sam (Leah Rosen)	Name_Albigona, Mr. Nassef Cassem	...	\
0	0.0	0.0	...	
1	0.0	0.0	...	
2	0.0	0.0	...	
3	0.0	0.0	...	
4	0.0	0.0	...	
..	

886	0.0	0.0	...
887	0.0	0.0	...
888	0.0	0.0	...
889	0.0	0.0	...
890	0.0	0.0	...

	Title_Major	Title_Master	Title_Miss	Title_Mlle	Title_Mme	Title_Mr	\
0	0.0	0.0	0.0	0.0	0.0	1.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	1.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	1.0	
..	
886	0.0	0.0	0.0	0.0	0.0	0.0	
887	0.0	0.0	1.0	0.0	0.0	0.0	
888	0.0	0.0	1.0	0.0	0.0	0.0	
889	0.0	0.0	0.0	0.0	0.0	1.0	
890	0.0	0.0	0.0	0.0	0.0	1.0	

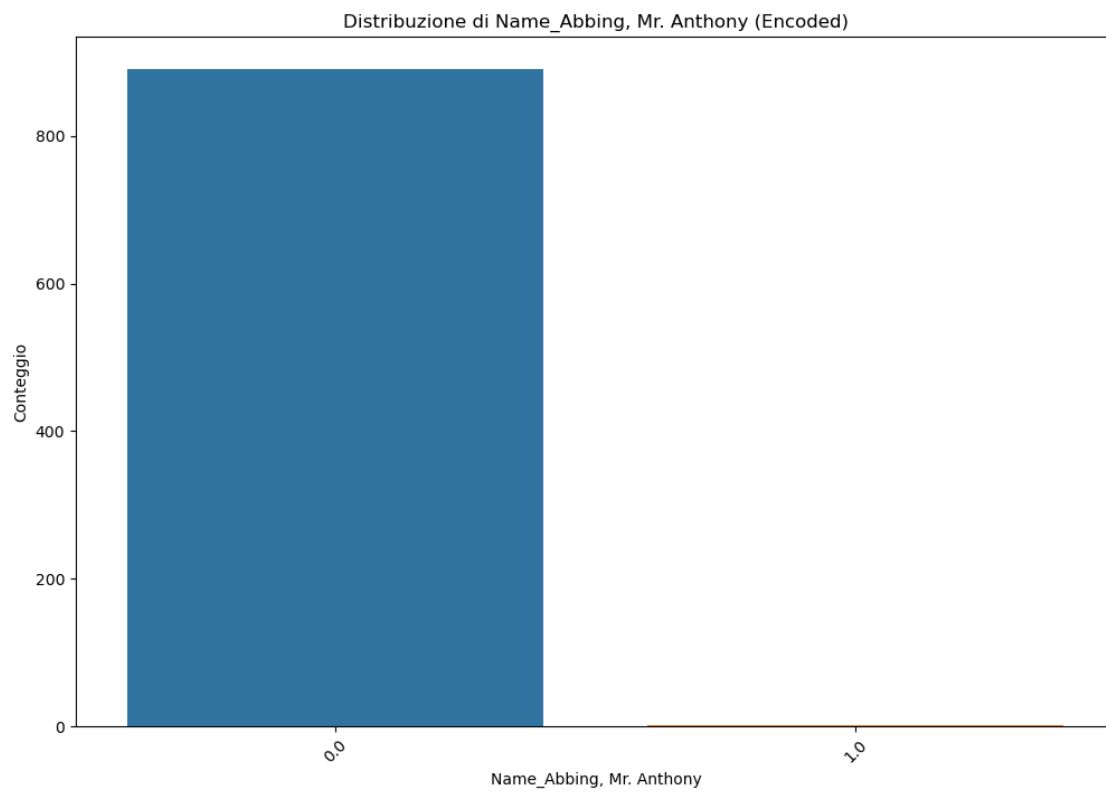
	Title_Mrs	Title_Ms	Title_Rev	Title_Sir
0	0.0	0.0	0.0	0.0
1	1.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	1.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0
..
886	0.0	0.0	1.0	0.0
887	0.0	0.0	0.0	0.0
888	0.0	0.0	0.0	0.0
889	0.0	0.0	0.0	0.0
890	0.0	0.0	0.0	0.0

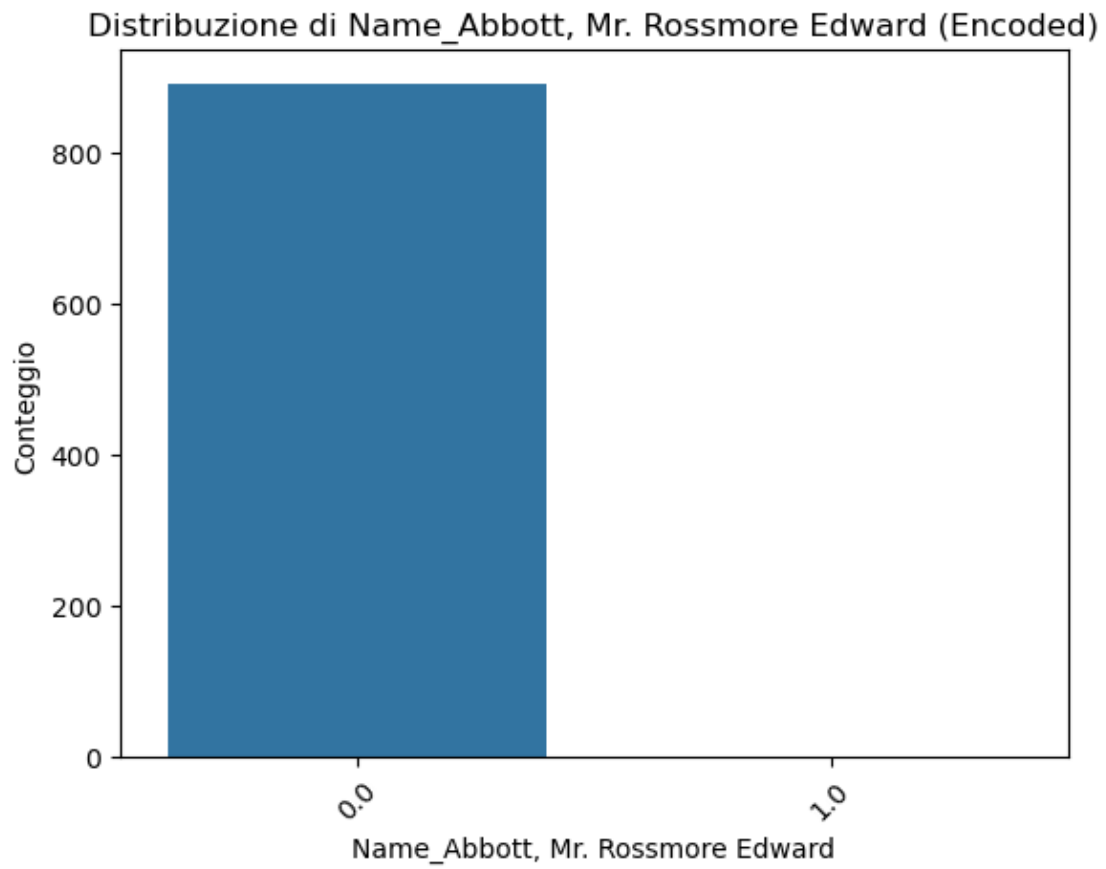
[891 rows x 1743 columns]

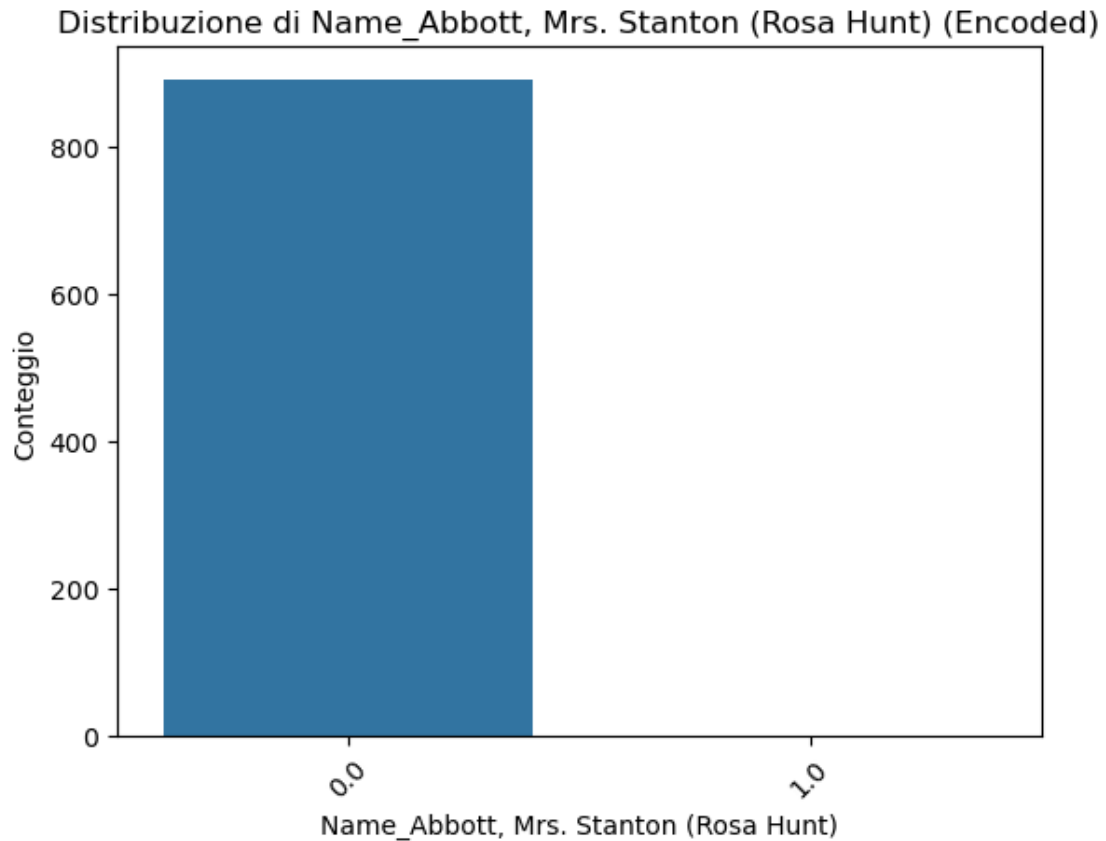
1.1.19 ITERAZIONE SUI PRIMI 3 PASSEGGERI SULLA LORO SOPPRAVVIVENZA O MORTE

```
[26]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, OneHotEncoder
# Quindi, abbiamo df2_scaled per le colonne numeriche scalate e df2_encoded per
↳ le colonne categoriche codificate
# Visualizzazione delle distribuzioni delle colonne categoriche codificate
↳ utilizzando grafici a barre
colonne = list(df2_encoded.columns[:3])
plt.figure(figsize=(12, 8))
```

```
for col in colonne:
    sns.countplot(data=df2_encoded, x=col)
    plt.title(f'Distribuzione di {col} (Encoded)')
    plt.xlabel(col)
    plt.ylabel('Conteggio')
    plt.xticks(rotation=45)
    plt.show()
```







1.1.20 CONTROLLO DEL DATAFRAME CODIFICATO PER CONTROLLARE SE E' CODIFICATO CORRETTAMENTE

```
[22]: df2_encoded
```

```
[22]:
```

	Name_Abbing, Mr. Anthony	Name_Abbott, Mr. Rossmore Edward \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0
890	0.0	0.0

	Name_Abbott, Mrs. Stanton (Rosa Hunt)	Name_Abelson, Mr. Samuel \
0	0.0	0.0

1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0
890	0.0	0.0

	Name_Abelson, Mrs. Samuel (Hannah Witosky) \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
886	0.0
887	0.0
888	0.0
889	0.0
890	0.0

	Name_Adahl, Mr. Mauritz Nils Martin	Name_Adams, Mr. John \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
886	0.0	0.0
887	0.0	0.0
888	0.0	0.0
889	0.0	0.0
890	0.0	0.0

	Name_Ahlin, Mrs. Johan (Johanna Persdotter Larsson) \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
..	...
886	0.0
887	0.0
888	0.0

889	0.0
890	0.0

	Name_Aks, Mrs. Sam (Leah Rosen)	Name_Alhimona, Mr. Nassef Cassem	...	\
0	0.0	0.0	...	
1	0.0	0.0	...	
2	0.0	0.0	...	
3	0.0	0.0	...	
4	0.0	0.0	...	
..	
886	0.0	0.0	...	
887	0.0	0.0	...	
888	0.0	0.0	...	
889	0.0	0.0	...	
890	0.0	0.0	...	

	Title_Major	Title_Master	Title_Miss	Title_Mlle	Title_Mme	Title_Mr	\
0	0.0	0.0	0.0	0.0	0.0	1.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	1.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	1.0	
..	
886	0.0	0.0	0.0	0.0	0.0	0.0	
887	0.0	0.0	1.0	0.0	0.0	0.0	
888	0.0	0.0	1.0	0.0	0.0	0.0	
889	0.0	0.0	0.0	0.0	0.0	1.0	
890	0.0	0.0	0.0	0.0	0.0	1.0	

	Title_Mrs	Title_Ms	Title_Rev	Title_Sir
0	0.0	0.0	0.0	0.0
1	1.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	1.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0
..
886	0.0	0.0	1.0	0.0
887	0.0	0.0	0.0	0.0
888	0.0	0.0	0.0	0.0
889	0.0	0.0	0.0	0.0
890	0.0	0.0	0.0	0.0

[891 rows x 1743 columns]

1.1.21 USO DELLA RANDOMFORESTCLASSIFIER

```
[23]: from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Definisci la variabile target
target_variable = titanic['Survived']

# Rimuovi la variabile target dal DataFrame codificato
X = df2_encoded
y = target_variable

# Suddivisione dei dati in training e testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Inizializza il classificatore Random Forest
rf_classifier = RandomForestClassifier(random_state=42)

# Addestra il modello sul set di dati di addestramento
rf_classifier.fit(X_train, y_train)

# Effettua le predizioni sul set di dati di test
y_pred = rf_classifier.predict(X_test)

# Valuta le prestazioni del modello
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Visualizza l'accuratezza e il report di classificazione
print("Accuratezza del modello:", accuracy)
print("\nReport di classificazione:\n", classification_rep)
```

Accuratezza del modello: 0.8156424581005587

Report di classificazione:

	precision	recall	f1-score	support
0	0.83	0.86	0.85	105
1	0.79	0.76	0.77	74
accuracy			0.82	179
macro avg	0.81	0.81	0.81	179
weighted avg	0.81	0.82	0.82	179

1.1.22 USO DELLA SUPPORT VECTOR CLASSIFIER

```
[24]: from sklearn.model_selection import train_test_split
from sklearn.svm import SVC # Import Support Vector Classifier
from sklearn.metrics import accuracy_score, classification_report

# Definisci la variabile target
target_variable = titanic['Survived']

# Rimuovi la variabile target dal DataFrame codificato
X = df2_encoded
y = target_variable

# Suddivisione dei dati in training e testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Inizializza il classificatore SVM
svm_classifier = SVC(random_state=42) # Utilizza SVC invece di
↳RandomForestClassifier

# Addestra il modello sul set di dati di addestramento
svm_classifier.fit(X_train, y_train)

# Effettua le predizioni sul set di dati di test
y_pred = svm_classifier.predict(X_test)

# Valuta le prestazioni del modello
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Visualizza l'accuratezza e il report di classificazione
print("Accuratezza del modello:", accuracy)
print("\nReport di classificazione:\n", classification_rep)
```

Accuratezza del modello: 0.8100558659217877

Report di classificazione:

	precision	recall	f1-score	support
0	0.83	0.85	0.84	105
1	0.78	0.76	0.77	74
accuracy			0.81	179
macro avg	0.80	0.80	0.80	179
weighted avg	0.81	0.81	0.81	179

1.1.23 USO DELLA LOGISTIC REGRESSION

```
[25]: from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Definisci la variabile target
target_variable = titanic['Survived']

# Rimuovi la variabile target dal DataFrame codificato
X = df2_encoded
y = target_variable

# Suddivisione dei dati in training e testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)

# Inizializza il classificatore di regressione logistica
log_reg_classifier = LogisticRegression(random_state=42)

# Addestra il modello sul set di dati di addestramento
log_reg_classifier.fit(X_train, y_train)

# Effettua le predizioni sul set di dati di test
y_pred = log_reg_classifier.predict(X_test)

# Valuta le prestazioni del modello
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Visualizza l'accuratezza e il report di classificazione
print("Accuratezza del modello:", accuracy)
print("\nReport di classificazione:\n", classification_rep)
```

Accuratezza del modello: 0.8212290502793296

Report di classificazione:

	precision	recall	f1-score	support
0	0.84	0.86	0.85	105
1	0.79	0.77	0.78	74
accuracy			0.82	179
macro avg	0.82	0.81	0.81	179
weighted avg	0.82	0.82	0.82	179